Chapter 3

Image Splicing Detection

3.1 Preamble

Forensic experts believe that no criminal can do his activities without leaving evidence at the scene of crime. However it is very difficult to trace out evidences especially in case of digital image forgeries. Nowadays, image content manipulation is a serious issue in digital image forensics. Among the numerous ways of image tampering, image splicing is a common form of image forgery. A spliced (or composite) image is usually created by copying and pasting portions of the image onto the same or another image. However, if such images are abused, it may give rise to some serious problems which potentially may have deep moral, ethical and legal implications. Hence, image content authentication has become an important issue.

Digital signature and watermarking have been proposed as the means to authenticate the contents of digital images. These techniques are called active techniques. However, signature and watermark based methods require some pre-processing such as signature generation and watermark embedding when creating the images, which would limit their applications in practice. Thus, they

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Some parts of the material in this chapter have appeared in the following research papers


are active techniques. On the other hand, passive techniques for image forensics operate in the absence of any watermark or signature. These techniques work on the assumption that although digital forgeries may leave no visual clues which indicate tampering, they may alter the underlying statistics of the image.

Any untampered image must have two common properties, viz. natural scene quality and natural imaging quality (Ng et al., 2005). For example, an image with inconsistency between the light direction and the shadow is not authentic because it fails to satisfy natural scene quality. Any output image naturally inherits the characteristic properties of the acquisition device. An image generated does not meet the natural imaging quality if different parts of the image do not share consistent characteristics of imaging device. A skilled forger can manage to satisfy the natural scene quality by using sophisticated image editing software but natural imaging quality is very difficult to achieve.

Usually a composite image is created not just by weaving different portions of the same or different images, but is also accompanied by subsequent operations like JPEG compression, contrast/brightness adjustment, color changing, blurring, rotation, resizing, etc. to hide the obvious traces of tampering. Consequently, image splicing detection has been considered as one of the most challenging problems in passive image content authentication. Unfortunately, no universal technique is available to detect splicing operation in all spliced images. Each forensic tool is developed based on understanding of, how does a specific form of tampering disturbs certain statistics of an image. Such forensic tools for investigating the problem of image splicing detection can be classified as pixel-based and camera-based techniques. The pixel-based techniques for image splicing detection are based on statistical anomalies introduced at the pixel level (Johnson and Farid, 2005; Ng et al., 2004; Ng and Chang, 2004; Popescu and Farid, 2005a; Chen et al., 2007b). The camera-based techniques for image splicing detection are based on inherent characteristics of the camera (Popescu and Farid, 2005b; Johnson and Farid, 2006; Lukáš et al., 2006a; Hsu and Chang, 2006; Johnson and Farid, 2007a; Li et al., 2009). In this chapter, we investigate a new camera-based technique for the detection of image splicing.
3.2 Background

One of the kinds of image tampering is object removal where the regions of unwanted objects in an image are replaced by other parts of the same image. This type of operation is called copy-move forgery or region duplication. The methods (Fridrich et al., 2003; Popescu and Farid, 2004; Luo et al., 2006) based on block matching are specifically designed to detect region duplication. First, the method divides an image into small blocks. Then it extracts the features from each block and hence, identifies possible duplicated regions by comparison. The main difference between these methods is the choice of features. Fridrich et al. (2003) have analyzed the Discrete Cosine Transform (DCT) coefficients from each block. Popescu and Farid (2004) have employed the Principal Component Analysis (PCA) to reduce the image blocks into a PCA feature vector. Luo et al. (2006) have extracted seven features in each block. Their experimental results demonstrated that the method could resist more post-processing operations.

Another kind of image tampering is splicing. Unlike region duplication, image splicing is defined as a simple joining of fragments of two or more different images. Several researchers have investigated the problem of splicing based on statistical properties of pixels (called pixel-based techniques) and camera characteristics (called camera-based techniques). Now, let us briefly review the literature on both techniques.

Johnson and Farid (2005) have described a method for revealing traces of tampering using light inconsistencies as it is often difficult to match the lighting conditions from the individual photographs. Ng et al. (2004) have described techniques to detect photomontaging. They have designed a classifier based on bi-coherence features of the natural images and photomontaged images. A mathematical model for image splicing is proposed by Ng and Chang (2004). One of the fundamental operations that need to be carried out in order to create forgeries is resizing (resampling). It is an operation that is likely to be carried out irrespective of the kind of forgery (copy move, photomontage, etc). Popescu and Farid (2005a) have described a method for estimating resampling parameters in a
discrete sequence and have shown its applications to image forensics. Chen et al. (2007b) have analyzed phase congruency for detection of image splicing.

The camera-based techniques for image splicing detection are based on inherent characteristics of the camera. Johnson and Farid (2006) have explored lateral chromatic aberration as a tool for detecting image tampering. Lateral chromatic aberration manifests itself, to a first-order approximation, as an expansion/contraction of color channels with respect to one another. When tampering with an image, this aberration is often disturbed and fails to be consistent across the image. As the authors have mentioned, this approach is effective only when the manipulated region is relatively small allowing for a reliable global estimate. Copy-paste forgery in JPEG images has been detected by extracting the DCT block artifact grid and by identifying mismatch among the grid (Li et al., 2009). Popescu and Farid (2005b) have noticed that the color images taken from a digital camera have specific kind of correlations among the pixels, due to interpolation in the color filter array (CFA). These correlations are likely to be destroyed, when an image is tampered. They have shown that the method can reasonably distinguish between CFA and non-CFA interpolated portions of images even when the images are subjected to JPEG compression, additive noise or luminance non-linearities. But they have not discussed splice detection, when portions of different images with same CFA interpolation technique are spliced together to form a composite image. Lukáš et al. (2006a) have presented an automatic approach for the detection of tampered regions based on pattern noise, a unique stochastic characteristic of imaging sensors. The regions that lack the pattern noise are highly suspected to be forgeries. The method works in the presence of either the camera that took the image or when sufficient number of images taken by that camera are available. However, this is always not possible. A semi-automatic method for detection of image splicing based on geometry invariants and camera characteristic consistency have been proposed by Hsu and Chang (2006). The method detects Camera Response Function (CRF) for each region in an image based on geometry invariants and subsequently checks whether the CRFs are consistent with each other using cross-fitting techniques. Because
inconsistency in CRFs indicate splicing. The authors have used only uncompressed RAW or BMP image formats which are not always provided with all consumer level compact digital cameras, whereas the proposed approach in this chapter, is not restricted to the type of image format. Johnson and Farid (2007a) have described a technique specifically designed to detect composites of images of people. This approach estimates a camera’s principal point from the image of a person’s eyes. Inconsistencies in the principal point are then used as evidence of tampering. As mentioned by the authors, the major sensitivity with this technique is in extracting the elliptical boundary of the eye. This process will be particularly difficult in low-resolution images.

This chapter demonstrates that it is possible to use inherent lens aberrations as unique fingerprints in images for the detection of image splicing. The proposed method uses camera characteristic property; lens radial distortion for splicing detection. The proposed method can successfully detect both copy-move and copy-paste forgery even if they are created by using images of the same camera.

### 3.3 Lens Radial Distortion

Virtually all optical imaging systems introduce a variety of aberrations into an image due to its imperfections and artifacts. Lens distortion is one such aberration introduced due to the geometry of camera lenses. Unlike extrinsic factors, intrinsic factors are due to camera characteristics and are specific constants to a camera, e.g. focal length, imaging plane position and orientation, lens distortion, aspect ratio etc. These are independent of camera’s position and nature of the objects captured. Lens distortion is deviation from rectilinear projection: a projection, in which the straight lines in a scene remain straight in an image. However, in reality almost all lenses suffer from small or large amounts of distortion. Lens radial distortion is the dominating source of mapping errors especially in inexpensive wide-angle lenses because wide-angle lens is shaped to allow a larger field of view. Figure 3.1 shows some examples of images which suffer from lens radial distortion.

Due to the shape of the lens (i.e spherical), magnification and focus is not isotropic
resulting in unwanted distortions. Lens radial distortion deforms the whole image by rendering straight lines in the object space as curved lines on the film or camera sensor. Radial distortion is a non-linear transformation of the image increasing from the center of distortion to the periphery of the image. The center of lens distortion is a point somewhere close to the center of the image, around which distortion due to the shape of the camera lens is approximately symmetrical.

Figure 3.2(a) shows an image of a grid and its radius \(r\). Two of the most common distortions are barrel (\(k>0\)) and pincushion (\(k<0\)) distortions (shown in Figure 3.2(b) and 3.2(c)), where \(k\) is the distortion parameter which indicates the amount of lens radial distortion. \(r'\) in Figure 3.2(b) and 3.2(c) are the deformed radii of the grid due to distortions.

It is evident from Figure 3.2(b) and 3.2(c) that the amount of distortion increases with the distance from center of image to the periphery of image and this property may be disturbed in spliced images. In the current investigation, to prove the integrity of an image, we look for the consistency among the degree of lens distortion.
radial distortion, estimated from different portions of the image. This source of information is very strong, provided 3D lines are projected on the image. Thus, the proposed technique works on images of city scene, interior scenes, aerial views containing buildings and man-made structures. Apart from the lens design, the degree of radial distortion is related to focal length (Choi et al., 2006a). Usually, lenses with short focal length have a larger degree of barrel distortion, whereas lenses with long focal length suffer more from pincushion distortion. Consequently, lenses from different camera leave unique imprints on the images being captured.

3.3.1 Estimation of Lens Radial Distortion

The lens radial distortion model can be written as an infinite series, as given below:

\[
r_u = r_d(1 + k_1 r_d^2 + k_2 r_d^4 + \cdots)
\]  

(3.1)

where \( r_u = \sqrt{x_u^2 + y_u^2} \), \( r_d = \sqrt{x_d^2 + y_d^2} \)

\( r_u, r_d \) are undistorted and distorted radii respectively. Radius is the radial distance \( \sqrt{x^2 + y^2} \) of a point \( (x,y) \) from the center of distortion. From equation 3.1 it follows that:

\[
x_u = x_d(1 + k_1 r_d^2 + k_2 r_d^4 + \cdots)
\]  

(3.2)

\[
y_u = y_d(1 + k_1 r_d^2 + k_2 r_d^4 + \cdots)
\]  

(3.3)

Center of distortion is taken as center of image (Choi et al., 2006a). The first order radial symmetric distortion parameter \( k_1 \) is sufficient for reasonable accuracy in the estimation of radial distortion (Deverney and Faugeras, 2001). Thus, the polynomial distortion model in equation 3.2 and 3.3 may be simplified as

\[
x_u = x_d(1 + k_1 r_d^2)
\]  

(3.4)

\[
y_u = y_d(1 + k_1 r_d^2)
\]  

(3.5)

The parameter \( k_1 \) has dominant influence on the kind of radial distortion. If \( k_1 > 0 \), distortion is barrel and if \( k_1 < 0 \), distortion is pincushion.
3.4 Proposed Approach

Portions of an image are correlated with each other with respect to the imaging device. Such correlations will be disturbed in spliced images. An intrinsic camera parameter viz., lens radial distortion is used for the detection of image splicing. Inconsistency in the degree of lens radial distortion across the image is the main evidence for splicing operation. In this section, a novel passive technique is described for detecting copy-paste forgery by quantitatively measuring lens radial distortion from different portions of the image using line-based calibration.

Line-based calibration of lens radial distortion can be divided into three steps:

1. Detection of edges with sub-pixel accuracy
2. Extraction of distorted line segments
3. Estimation of $k_1$ for each distorted line in an image

Detection of edges with sub-pixel accuracy: The first step of the calibration consists of detecting edges from an image. Since image distortion is sometimes less than a pixel, there is a need for an edge detection method with sub-pixel accuracy. This work uses an edge detection method proposed by Deverney (1995), which is a sub-pixel refinement of the classic non-maxima suppression of the gradient norm in the direction of the gradient.

Extraction of distorted line segments: This calibration method relies on the constraint that straight lines in 3D must always project to straight lines in the 2D image plane, if the radial lens distortion is compensated. In order to calibrate distortion, we must find edges in the image which are most probably projections of 3D line segments. Due to distortion, a long segment may be broken into smaller segments. By defining a very small tolerance region, we can extract such distorted line segments as shown in Figure 3.3. Perturbations in the line segments may be expected in low resolution images. Such distracted or perturbed line segments must be rejected even if they are within the tolerance region.

Estimation of $k_1$ for each distorted line in an image: Measure the degree
Figure 3.3: Detection of broken line segments within the tolerance region of distortion for each distorted line in the image. In order to measure the absolute deviation of a distorted line from its undistorted line, the points on a distorted line segment are used to fit a straight line using linear regression (Thormhlen et al., 2003).

From equation 3.4 and 3.5, all ‘n’ distorted points \( p_{d,i} = (x_{d,i}, y_{d,i}) \) of the selected curved line are mapped to the undistorted points \( p_{u,i} = (x_{u,i}, y_{u,i}) \) where \( 1 \leq i \leq n \) as follows:

\[
x_{u,i} = x_{d,i}(1 + k_1 r_{d,i}^2) \tag{3.6}
\]
\[
y_{u,i} = y_{d,i}(1 + k_1 r_{d,i}^2) \tag{3.7}
\]

All ‘n’ undistorted points \( p_{u,i} \) should now lie on a straight line. Thus, an associated straight line ‘\( L_n \)’ is represented in Hesse’s normal form, it has three unknowns \( n_x \), \( n_y \) and \( d_0 \):

\[
L_n : \begin{pmatrix} n_x \\ n_y \end{pmatrix}^T \begin{pmatrix} x \\ y \end{pmatrix} - d_0 = 0 \tag{3.8}
\]

To determine these unknowns with linear regression, the following expressions are used.

\[
\bar{X} = \frac{1}{n} \sum_{i=1}^{n} x_{d,i} \quad \bar{Y} = \frac{1}{n} \sum_{i=1}^{n} y_{d,i} \quad \bar{X}^2 = \frac{1}{n} \sum_{i=1}^{n} (x_{d,i})^2 \quad \bar{Y}^2 = \frac{1}{n} \sum_{i=1}^{n} (y_{d,i})^2 \quad \bar{XY} = \frac{1}{n} \sum_{i=1}^{n} x_{d,i} y_{d,i}
\]

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There are two cases to be distinguished:

Case 1: Let $X^2 - (\bar{X})^2 \geq Y^2 - (\bar{Y})^2$, then the associated straight line $L_n$ is parameterized as

$$L_n : y = ax + b$$

where

$$a = \frac{XY - \bar{X} \bar{Y}}{X^2 - (\bar{X})^2} \quad b = \frac{X^2 \bar{Y} - \bar{X} XY}{X^2 - (\bar{X})^2}$$

and the three unknowns are as follows:

$$n_x = \frac{-a}{\sqrt{a^2 + 1}} \quad n_y = \frac{1}{\sqrt{a^2 + 1}} \quad d_0 = \frac{b}{\sqrt{a^2 + 1}}$$

Case 2: Let $X^2 - (\bar{X})^2 < Y^2 - (\bar{Y})^2$, then the parameterizations of the associated straight line $L_n$ changes to:

$$L_n : x = cy + d$$

where

$$c = \frac{XY - \bar{X} \bar{Y}}{Y^2 - (\bar{Y})^2} \quad d = \frac{X^2 \bar{Y} - \bar{X} XY}{Y^2 - (\bar{Y})^2}$$

In this case the three unknowns of equation 3.8 are

$$n_x = \frac{1}{\sqrt{c^2 + 1}} \quad n_y = \frac{-c}{\sqrt{c^2 + 1}} \quad d_0 = \frac{d}{\sqrt{c^2 + 1}}$$

Now, an associated straight line $L_n$ is found, which is a function of $k_1$ and the points $p_{d,i}$. Thus, a cost function with the residual errors $\varepsilon_i$ of equation 3.8 is formulated as:

$$\varepsilon_i : \begin{pmatrix} n_x \\ n_y \end{pmatrix}^T \begin{pmatrix} x_{u,i} \\ y_{u,i} \end{pmatrix} - d_0$$

Substitute $x_{u,i}$ and $y_{u,i}$ from equation 3.6 and 3.7

$$\varepsilon_i : \begin{pmatrix} n_x \\ n_y \end{pmatrix}^T \begin{pmatrix} x_{d,i}(1 + k_1 r_{d,i}^2) \\ y_{d,i}(1 + k_1 r_{d,i}^2) \end{pmatrix} - d_0$$
where \( k_1 \) is selected to minimize \( \sum_{i=1}^{n} \varepsilon_i^2 \).

The above cost function is a non-linear function of \( x_{d,i} \) and \( y_{d,i} \) of a curved line or distorted line. The deviation of points \((x_{d,i}, y_{d,i})\) from their original positions \((x_{u,i}, y_{u,i})\) is used to estimate the amount of distortion. The distortion error is the sum of squares of distances from the points to the straight line. To estimate distortion parameter \( k_1 \) the sum of squares is minimized using the iterative Levenberg-Marquardt method through \textit{lsqnonlin} function found in MATLAB. Thus, we get unique \( k_1 \) for each distorted line segment in the image depending on the amount of distortion.

### 3.5 Experimental Study

Three sets of experiments were performed. The first set of experiments aimed at technical investigation and calibration of lens radial distortion in different consumer level compact digital cameras. The second set of experiments conducted on synthetic images to show how to use radial distortion parameter as a feature to detect image splicing. The purpose of third set of experiments is to measure the performance of proposed features on real images.

#### 3.5.1 Analysis of Lens Radial Distortion

To analyze the behavior of intrinsic radial distortion parameter across the image, we have used six digital cameras of recent models from four different manufacturers. The configurations of the cameras are given in Table 3.1.

Figure 3.4(a) shows the checker-board with 9 by 12 square grids, generated manually without any distortions. Figure 3.4(b) shows the extracted straight lines from Figure 3.4(a). The lens radial distortion parameter \( k_1 \) is computed for each straight line (refer Section 3.4) and is reported as zero for all straight lines and the same is shown as a graph in Figure 3.4(c). All through the experiments, it is assumed that the image center as \((0,0)\) and the horizontal and vertical coordinates are normalized so that the maximum of the dimensions is in the range \((-1,1)\). Most consumer digital cameras are equipped with an optical zoom lens. The lens radial
Table 3.1: Cameras used in experiments and their properties

<table>
<thead>
<tr>
<th>Camera Brand</th>
<th>Focal Length (mm)</th>
<th>Optical Zoom</th>
<th>Resolution (MP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sony DSC-W35</td>
<td>38-114</td>
<td>3x</td>
<td>7.2</td>
</tr>
<tr>
<td>Sony DSC-W220</td>
<td>29.7-118.8</td>
<td>4x</td>
<td>12.1</td>
</tr>
<tr>
<td>Canon A550</td>
<td>35-140</td>
<td>4x</td>
<td>7.1</td>
</tr>
<tr>
<td>Casio EX-Z75</td>
<td>38-114</td>
<td>3x</td>
<td>7.1</td>
</tr>
<tr>
<td>Nikon S550</td>
<td>36-180</td>
<td>5x</td>
<td>10</td>
</tr>
<tr>
<td>Sony DSC-W180</td>
<td>35-105</td>
<td>3x</td>
<td>10.1</td>
</tr>
</tbody>
</table>

Note: The focal length is equivalent to a 35mm film camera.

distortion parameters change with focal length, which usually varies from barrel at the wide end to pincushion at the tele end. In this section, we investigate the impact of optical zoom on the behavior of radial distortion parameter across the image.

![Checker-board](image1.png)

![Extracted edges](image2.png)

![Graph of k1](image3.png)

**Figure 3.4:** (a) Checker-board (b) Extracted edges and (c) Graph of $k_1$ for each line in (b)
To study the actual behavior of radial distortion parameter $k_1$ across the image, images of the same scene are acquired from different cameras. The checker board (shown in Figure 3.4(a)) is captured, approximately with same distance, position and orientation of the camera. The images were taken with no flash, auto-focus, JPEG format and other default settings. The sample images captured by Sony DSC-W35 camera with different zoom levels are shown in Figure 3.5. Figure 3.6 is the corresponding edge images of each image in Figure 3.5. Since the radial distortion is approximately symmetric, the graph of $k_1$ is drawn for vertical lines which lies in the right of image center. Figure 3.7 shows the behavior of radial distortion parameter $k_1$ across the image for various cameras at different zoom levels. It is clear that no camera is ideal. All cameras have noticeable amount of radial distortion. It is evident from the graph that the degree of radial distortion increases with the distance from center of the image. We can also observe that the radial distortion parameter changes with zoom and most of the cameras varies from barrel at the wide end to pincushion at the tele end (refer graphs (a), (b), (d) and (f) in Figure 3.7).

![Figure 3.5: Checker-board image captured by Sony DSC-W35 camera](image)

![Figure 3.6: Extracted edges from Figure 3.5](image)
3.5.2 Experiments on Synthetic Images

This section describes how to use lens radial distortion parameter for the detection of image splicing. If two image regions belong to the same (untampered) image, then the radial distortion of extracted line segments should behave as expected (explained in Section 3.5.1). i.e. lines that are more or less equidistant will suffer from more or less equal amount of radial distortion. Also radial distortion is uniform, barrel or pincushion.

Normally the composite images are created in three ways:
(i) Image splicing on the same image (Copy-move forgery)

(ii) Two or more images of the same camera (may be captured at different zoom) are used to create a composite image

(iii) Two or more images of the different cameras (irrespective of the camera make or model) are used to create a spliced image

Hence, we used three different cameras, in which two are from the same manufacturer, so that all types of splicing described above can be carried out. Figure 3.8(a) is the image acquired from Sony DSC-W35 and the extracted straight lines are shown in Figure 3.8(b). Table 3.2 shows the distances (column 2) of straight lines from the image center and its corresponding values of $k_1$ (column 3).

Line 1 is the left most and line 6 is the right most line. Now, we can observe that the values of $k_1$ gradually increase from image center to its periphery. Similar observations on $k_1$ were already noticed in Section 3.5.1 (refer graphs in Figure3.7). This consistency will be disturbed in case of copy-move or copy-paste forgery. Inconsistency in lens radial distortion can be detected if one of the two conditions is not met: (a) amount of radial distortion is symmetric and increases with the distance from center of the image and (b) sign of $k_1$ should be the same for all lines throughout the image.

**Table 3.2:** Estimated $k_1$ for each line (from left to right) in Figure 3.8(b)

<table>
<thead>
<tr>
<th>Straight line no.</th>
<th>Distance from center</th>
<th>Distortion parameter $k_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.4095</td>
<td>0.01439</td>
</tr>
<tr>
<td>2</td>
<td>-0.1727</td>
<td>0.00455</td>
</tr>
<tr>
<td>3</td>
<td>-0.1139</td>
<td>0.00065</td>
</tr>
<tr>
<td>4</td>
<td>0.1181</td>
<td>0.00071</td>
</tr>
<tr>
<td>5</td>
<td>0.1809</td>
<td>0.00478</td>
</tr>
<tr>
<td>6</td>
<td>0.4112</td>
<td>0.01485</td>
</tr>
</tbody>
</table>

In the untampered image (Figure 3.8(a)), all bottles are of different colors. The
composites were created by copying and pasting a bottle over another bottle. The different cases of image splicing described in (i) to (iii) are shown in Figure 3.9. The original images were captured at different zoom levels and some post-processing operations like rotation and scaling have also been done while pasting a portion. The values of $k_1$ for each line from left to right for images in Figure 3.9 are listed in Tables 3.3 to 3.6, respectively.
### Table 3.3: Estimated $k_1$ for each line (from left to right) in Figure 3.9(a)

<table>
<thead>
<tr>
<th>Straight line no.</th>
<th>Distance from center</th>
<th>Distortion parameter $k_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.4736</td>
<td>-0.00371</td>
</tr>
<tr>
<td>2</td>
<td>-0.1981</td>
<td>-0.04611</td>
</tr>
<tr>
<td>3</td>
<td>-0.144</td>
<td>0.000923</td>
</tr>
<tr>
<td>4</td>
<td>0.1193</td>
<td>0.000872</td>
</tr>
<tr>
<td>5</td>
<td>0.1934</td>
<td>0.003192</td>
</tr>
<tr>
<td>6</td>
<td>0.4614</td>
<td>0.048074</td>
</tr>
</tbody>
</table>

### Table 3.4: Estimated $k_1$ for each line (from left to right) in Figure 3.9(b)

<table>
<thead>
<tr>
<th>Straight line no.</th>
<th>Distance from center</th>
<th>Distortion parameter $k_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.4688</td>
<td>0.038074</td>
</tr>
<tr>
<td>2</td>
<td>-0.2033</td>
<td>0.004531</td>
</tr>
<tr>
<td>3</td>
<td>-0.1447</td>
<td>-0.00172</td>
</tr>
<tr>
<td>4</td>
<td>0.1285</td>
<td>0.01014</td>
</tr>
<tr>
<td>5</td>
<td>0.1934</td>
<td>0.0043</td>
</tr>
<tr>
<td>6</td>
<td>0.4614</td>
<td>0.034251</td>
</tr>
</tbody>
</table>

### Table 3.5: Estimated $k_1$ for each line (from left to right) in Figure 3.9(c)

<table>
<thead>
<tr>
<th>Straight line no.</th>
<th>Distance from center</th>
<th>Distortion parameter $k_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.4704</td>
<td>-0.00077</td>
</tr>
<tr>
<td>2</td>
<td>-0.199</td>
<td>-0.00169</td>
</tr>
<tr>
<td>3</td>
<td>-0.1337</td>
<td>-0.001394</td>
</tr>
<tr>
<td>4</td>
<td>0.1247</td>
<td>-0.0128</td>
</tr>
<tr>
<td>5</td>
<td>0.1963</td>
<td>0.002672</td>
</tr>
<tr>
<td>6</td>
<td>0.4754</td>
<td>0.038046</td>
</tr>
</tbody>
</table>
Inconsistency is highlighted in all the tables. When a bottle on the right side is pasted over a bottle on the left side (shown in Figure 3.9(a)) then the radial distortion of the corresponding edges would change to barrel (pincushion), whereas the actual distortion in untampered image would have been pincushion (barrel). This can be noticed in Table 3.3. Image in Figure 3.9(b) has been spliced by replacing the middle bottle by a bottle on the right side of another image and \(k_1\) values for all extracted lines are given in Table 3.4. \(k_1\) is negative for line 3 and positive for all the other lines indicating inconsistency of type (b). Observe that \(k_1\) of line 4 is greater than that of line 5, this implies inconsistency of type (a). Thus, splicing has been successfully detected.

In real cases, the creation of composites is commonly accompanied with subsequent operations like JPEG compression, contrast/brightness adjustment, color changing, blurring, rotation, resizing etc. to hide the obvious traces of tampering. Since the proposed splicing detection method works on images consisting of straight edges, contrast, brightness and color manipulations will not affect edge detection, unless the object color and the background color are indistinguishable. It is evident from the above experiments that the proposed approach is robust to rotation, as distortion is same, even if lines are rotated. We observed that JPEG compression, blurring and resizing operations affect the performance of the proposed method. Experiments show that JPEG compression with a quality factor as low as 5 (out of 10) also can detect straight lines with

\[
\begin{array}{|c|c|c|}
\hline
\text{Straight line no.} & \text{Distance from center} & \text{Distortion parameter } k_1 \\
\hline
1 & -0.4798 & -0.107796 \\
2 & -0.2111 & -0.001981 \\
3 & -0.1464 & -0.001776 \\
4 & 0.1118 & -0.0008 \\
5 & 0.1782 & -0.00331 \\
6 & 0.4454 & 0.019655 \\
\hline
\end{array}
\]
reasonable accuracy sufficient to estimate \( k_1 \). Resizing is the most common operation performed while creating composites, in order to match with the size of host image. The proposed approach is robust to resizing and blurring provided the extracted lines continue to be unperturbed.

### 3.5.3 Experiments on Real Images

The non-availability of the suitable data set for examining the proposed method led us to create our own Spliced Image Data Set (SIDS). However, we have also experimented with a few images from the database provided by Hsu and Chang (2006). In order to compute the splice detection rate, 100 spliced images were created from 350 authentic images. Authentic images are taken with 6 consumer level compact digital cameras (mentioned in Table 3.1) and 50 images were downloaded from the internet. 50 images are captured from each of 6 cameras in JPEG format with dimensions ranging from 1632x1224 to 3072x2304.
Figure 3.10: (a)-(f) Sample spliced images and (g)-(l) their extracted edges
These images mainly contain indoor scenes like computers, boards, tables, library, photo frames etc. Some images contain outdoor scenes like buildings, shopping complex etc. Spliced images are created from the authentic image set using Adobe Photoshop. In order to hide the traces of tampering, post processing operations like resizing and rotation are performed.

![Image](a) ![Image](d) ![Image](b) ![Image](e) ![Image](c) ![Image](f)

**Figure 3.11:** (a)-(c) Sample images from database (Hsu and Chang, 2006) and (d)-(f) their extracted edges

As a first step, all distorted line segments from each spliced image are detected as described in Section 3.4. Further, for accurate comparison of distortion parameter $k_1$ for each detected line in an image, the length of those lines must be equal. All lines detected in an image are trimmed to that of the shortest line (at least one
third of the image height). The detection rate for our spliced image data set is found as 86%. Some sample spliced images of our data set and their extracted line segments are shown in Figure 3.10. The pasted portion is indicated by red lines.

The proposed approach is also experimented on images selected from Columbia Image Splicing Detection Evaluation Data set. However, we have selected those spliced images which contain straight edges. Some sample images are shown in Figure 3.11. The pasted portion is indicated by red lines. In all the images spliced portions are detected successfully.

3.6 Discussion

The proposed approach detects splicing of images when straight edges are available, but the main difficulty lies in the extraction of such straight edges. Sometimes the low resolution image will generate perturbations along the straight lines which results in wrong estimation of radial distortion parameter. Because of low resolution, an authentic image in Figure 3.12 is detected as spliced image (perturbations may be visible in enlarged version).

![Figure 3.12: (a) A low resolution image and (b) Extracted perturbed lines](image)

It is noticed that sometimes the proposed method may not provide sufficiently conclusive statistical evidence regarding spliced portions of the image. It means the proposed approach may fail to detect a spliced portion if two images have same kind of distortion are spliced together and the position of copied and pasted portion is same with respect to the center of image. Also, more research and analysis are needed to determine the influence of center of distortion and
the length of lines. Though the proposed method works for the images from lower-end consumer level digital cameras taken with default settings and most commonly available JPEG image format, we need at least two or more straight lines with the minimum length of one third of the image height from different regions in order to prove the integrity of the image. To summarize, the proposed method works best on images with a lot of lines and of significant lengths, such as images of city scenes, interior scenes, aerial views containing buildings and man-made structures. Probably the experimental results can be improved by using a more sophisticated method to estimate lens radial distortion across the image. We expect the proposed technique, when integrated with other available splicing detection methods (Johnson and Farid, 2006; Popescu and Farid, 2005b; Lukáš et al., 2006a; Hsu and Chang, 2006; Johnson and Farid, 2007a) to become more effective in exploring digital forgeries. It is interesting to address malicious attacks intended to interfere the detection algorithm, such as adding or removing radial distortion from an image (Farid and Popescu, 2001; Weng, 1992). Since, it is possible to manipulate the distortion parameters of an image globally, these alterations will not affect the performance of the proposed method if done on spliced image.

3.7 Conclusion

In this chapter, a novel method is proposed for detection of image splicing by estimating lens radial distortion from different portions of the image. Virtually all optical imaging systems introduce a variety of aberrations into an image. The majority of digital cameras are equipped with spherical lens and this introduces radial distortion on images. This aberration is often disturbed and fails to be consistent across the image, when an image is spliced. A polynomial model for measuring lens radial distortion on images is described. The experiments demonstrated that the spliced image may be detected even it is created by compositing one or more images of the same camera. Experiments in Section 3.5.1 showed that most consumer level digital cameras have small or large amount of lens radial distortion at different zoom levels. Experimental set up in Section 3.5.2
demonstrated how efficiently the lens radial distortion parameter $k_1$ may be used for the detection of image splicing and the experimental results in Section 3.5.3 shown that the proposed method works well in case of real images. The primary contribution of this research work is the examination of the use of inherent lens radial distortion as a unique imprint on images for the detection of image splicing.